THE ASSESSMENT OF STANDING BALANCE WITH SMARTPHONE TECHNOLOGY
FOR THE PREVENTION OF FALLS IN OLDER ADULTS

BY

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THESIS

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**ABSTRACT**

One in three adults over the age of 65 will fall in a year, and falls are the leading cause of accidental injury and injury related deaths in this population. Preventative measures to reduce falls include multifactorial fall risk assessments. Balance impairment is routinely used as a measure of fall risk. However, balance assessments require expensive research-grade equipment or clinical expertise. Mobile devices, such as smartphones, provide a potential platform for accessible and inexpensive fall risk assessments. Prior to being implemented in the fall prevention strategies, the concurrent validity, reliability, and usability of such devices needs to be established. The purpose of this thesis was to determine the concurrent validity of a novel smartphone based balance assessment application. Concurrent validity of the novel smartphone balance application was determined by comparing its ability to distinguish the standing balance of young healthy adults (n=15), older adults with low fall risk (as determined by the physiological profile assessment; n=13), and older adults with high fall risk (as determined by the physiological profile assessment; n=17) to the gold standard (force platform). The application was tested under seven different static balance conditions. Repeated measures ANOVAs were used to determine differences between groups on both force platform and smartphone measures. Spearman rank-order correlations were used to evaluate the relationship between force platform and smartphone measures. The Berg Balance Scale, Force platform measures (MVAP and MVRAD), and smartphone measures (Max Accel Y and RMS X) were able to distinguish between low risk and high risk older adults ($p \leq .05$). Spearman rank-order correlations demonstrated 32 moderate correlations ($.5 \leq \rho \leq .7$) and 9 strong correlations ($\rho \geq .7$) between force platform and smartphone measures. Eight high fall risk older adults were unable to complete all balance conditions, of those five were unable to complete multiple balance conditions. Differences in failure rates were significant between low fall risk older adults and high fall risk older adults. Despite the positive failure rates, no adverse events were recorded. Future research should evaluate additional smartphone accelerometry measures' ability to distinguish between fallers and non-fallers. It is concluded that smartphone based measures of balance are valid, and safe in older adults.

ACKNOWLEDGEMENTS

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**Table of Contents**

# CHAPTER 1: Introduction

## 1.1 Falls in Older Adults

One in three adults over the age of 65 will fall in a year (Control & Prevention, 2012), Falls are the leading cause of accidental injury and injury related deaths in individuals over 65 (Heinrich, Rapp, Rissmann, Becker, & König, 2010). Fall related injuries make up 0.85-1.5% of total healthcare expenditures in the U.S. (Heinrich et al., 2010). Beyond the fall itself, there is a high risk for a cycle of deconditioning that includes post fall-anxiety and a reduction in activity that might lead to future falls (Heinrich et al., 2010).

Furthermore, the population at risk for falls is growing. The number of individuals 60 years old and older is expected to be 2 billion by 2050 worldwide (Ageing & Unit, 2008). This presents a large need for effective fall prevention strategies to accommodate the growing senior population and reduce the number of falls, fall related injuries, and healthcare costs.

Fortunately, falls and fall risk factors can be reduced through targeted interventions (Pfortmueller, Lindner, & Exadaktylos, 2014). Successful interventions include a multifactorial risk assessment, exercise training, and environmental assessment and modifications (Rubenstein, 2006). A successful multifactorial fall risk assessment includes internal and external fall risk factors. Internal risk factors include physiological and psychological mechanisms. Physiological processes highly correlated with fall risk include gait and balance function, vision, proprioception, muscle strength, and vestibular function (Lord, Menz, & Tiedemann, 2003; Stelmach & Worringham, 1985).

Balance is often measured to determine fall risk in older adults (Ambrose, Paul, & Hausdorff, 2013). Qualitative and quantitative measures have been used to assess balance impairment in aging adults. Qualitative measures, such as the Berg Balance Scale, require the subjective assessment of balance on various tasks and a skilled professional to administer them (Shumway-Cook, Baldwin, Polissar, & Gruber, 1997). The technical skill to administer these tests makes them inaccessible to the average older adult. Quantitative measures of balance include accelerometry and posturography (Buatois, Gueguen, Gauchard, Benetos, & Perrin, 2006; Mayagoitia, Lötters, Veltink, & Hermens, 2002). However, these methods require expensive equipment. Ultimately, the need for clinical expertise and/or equipment significantly limits the availability of objective fall risk assessment for seniors.

Mobile technology such as smartphones and tablets offer a potential solution to the lack of access to fall risk assessment. In 2014, 21% of Americans over 65 owned a smartphone. That number grew to 27% in 2015 and continues to grow (Smith, 2015). Smartphones and tablets have sensors such as accelerometers and gyroscopes embedded within them (Amick, Patterson, & Jorgensen, 2013). These non-invasive sensors have the potential to measure static and dynamic motion along three axes. Indeed, standalone accelerometers and gyroscopes have been successfully used to measure balance (Moe-Nilssen & Helbostad, 2002; Wong & Wong, 2008).

Smartphone applications that measure balance and fall risk have the potential to meet an important need for aging individuals. The need for accessible, easy to use approaches to measure fall risk is increasing with the growing elderly population and their heightened risk for falls. This chapter systematically reviews the current state of smartphone based applications that measure balance in older adults and identifies a need for future research.

### 1.2 Systematic Review

The systematic review protocol described in the Preferred Reporting Items for Systemic Reviews and Meta-Analysis statement (Moher et al., 2015) were adopted to guide the review process.

*1.2.1 Eligibility Criteria*

To be included in the systematic review studies had to meet all of the following criteria– study design: randomized controlled trial (RCT), cohort study, pre-post study, or cross-sectional study; population: healthy adults over the age of 18; main outcomes: measures of balance and postural sway, accelerometry, posturography, and clinical balance measures where data collection happened via a mobile device such as a smartphone or tablet; article type: peer-reviewed publication; language: English. Studies were excluded from the review if meeting one or more of the following criteria – study design: review paper, non-human trials, and conference proceedings; systems that only measured fall detection; studies that only included measures of gait; non-English; and studies where a mobile device was not used to collect data.

*1.2.2 Information Sources*

Keyword search was performed in PubMed/Medline, Web of Science, and Cochrane Library. The search algorithm included all possible combinations of (1) "smartphone", "mobile", or "cell phone" (2) "falls", "fall", "balance", or "fall risk" and (3) "assessment", "aging", or "older adults". The specific search algorithm for each database is provided in appendix 1. Keywords were searched through January 2017 to February 2017. Article titles and abstracts were evaluated based on the search criteria. Articles that met the search criteria were saved for a full text evaluation. Forward and backward searches were also conducted on articles that met the inclusion criteria. Further articles found were also included for a full text read if they met the search criteria. An additional three articles were included following the forward/backward search.

*1.2.3 Study Records*

Article information was stored and sorted in Microsoft Excel version 1701 (Redmond, WA). KL Roeing and KL Hsieh reviewed each title and abstract independently to determine article inclusion/exclusion. Discrepancies were discussed with both parties and final decisions were made together.

*1.2.4 Data Extraction*

The following data was extracted from each article passing full text read: authors, publication year, study design, sample size, participant characteristics (healthy or neurologic population, age, and gender), data collection tools (smartphone, cell phone, tablet, accelerometer, force platform, and 3D motion capture), balance evaluation tests used, outcome measures collected, and results related to validity and reliability of collection tools. The following balance tests were used: static balance tests (feet parallel with eyes open, closed, dual tasking and on a foam surface; feet parallel with eyes closed on a firm surface; feet semi tandem with eyes open; feet tandem with eyes open, closed, and on a foam surface), and single leg stance; the Timed-Up-and-Go Test (TUG); the 30s chair test (how many times you can stand up and sit down in 30s); the Berg balance test; and the sit to stand test. Main outcome measures used included: balance: root mean square (RMS) of signal frequency, mean power frequency (MPF) of signal, angular velocity, trunk displacement, change in trunk angle, peak to peak amplitude displacement of signal, total signal frequency power, normalized path length, 95% ellipsoid volume, median signal frequency of power, and 95% spectral edge frequency; TUG: time, max change in trunk angle, max angular velocity, duration for separate elements (sit to stand, gait phase, turn, and stand to sit), RMS, jerk, mean and SD of stand time, and trunk movements; Berg: peak acceleration, sway area per second, mean distance of sway, and mean velocity of sway; 30s

Chair Test: angular velocity, displacement of the chest, and change in trunk angle; sit to stand: total time, peak force, rate of force development, and peak power.

## 1.3 Results

### *1.3.1 Study Selection*

Figure 1 depicts the article identification and selection process. There were 1,420 articles returned after the keyword search and 13 articles returned following the forward/backward search. After removing duplicate titles, there were 937 articles that underwent title and abstract screening. Following screening there were 28 articles that were read in full. A total of 15 articles were excluded after the full text read due to the following: did not use a mobile device to measure balance (n=4), only looked at fall detection with a mobile device (n=8), did not use human subjects (n=1), review paper (n=1), and conference proceedings (n=1). The remaining 13 articles were included in the review (Cerrito, Bichsel, Radlinger, & Schmid, 2015; Fleury et al., 2013; Franco et al., 2013; Galán-Mercant & Cuesta-Vargas, 2014; Kosse, Caljouw, Vervoort, Vuillerme, & Lamoth, 2015; Lee, Kim, Chen, & Sienko, 2012; Madhushri, Dzhagaryan, Jovanov, & Milenkovic, 2016; Mellone, Tacconi, & Chiari, 2012; Milosevic, Jovanov, & Milenković, 2013; Ozinga & Alberts, 2014; Ozinga, Machado, Miller Koop, Rosenfeldt, & Alberts, 2015; Tacconi, Mellone, & Chiari, 2011; Wai, Duc, Syin, & Zhang, 2014).

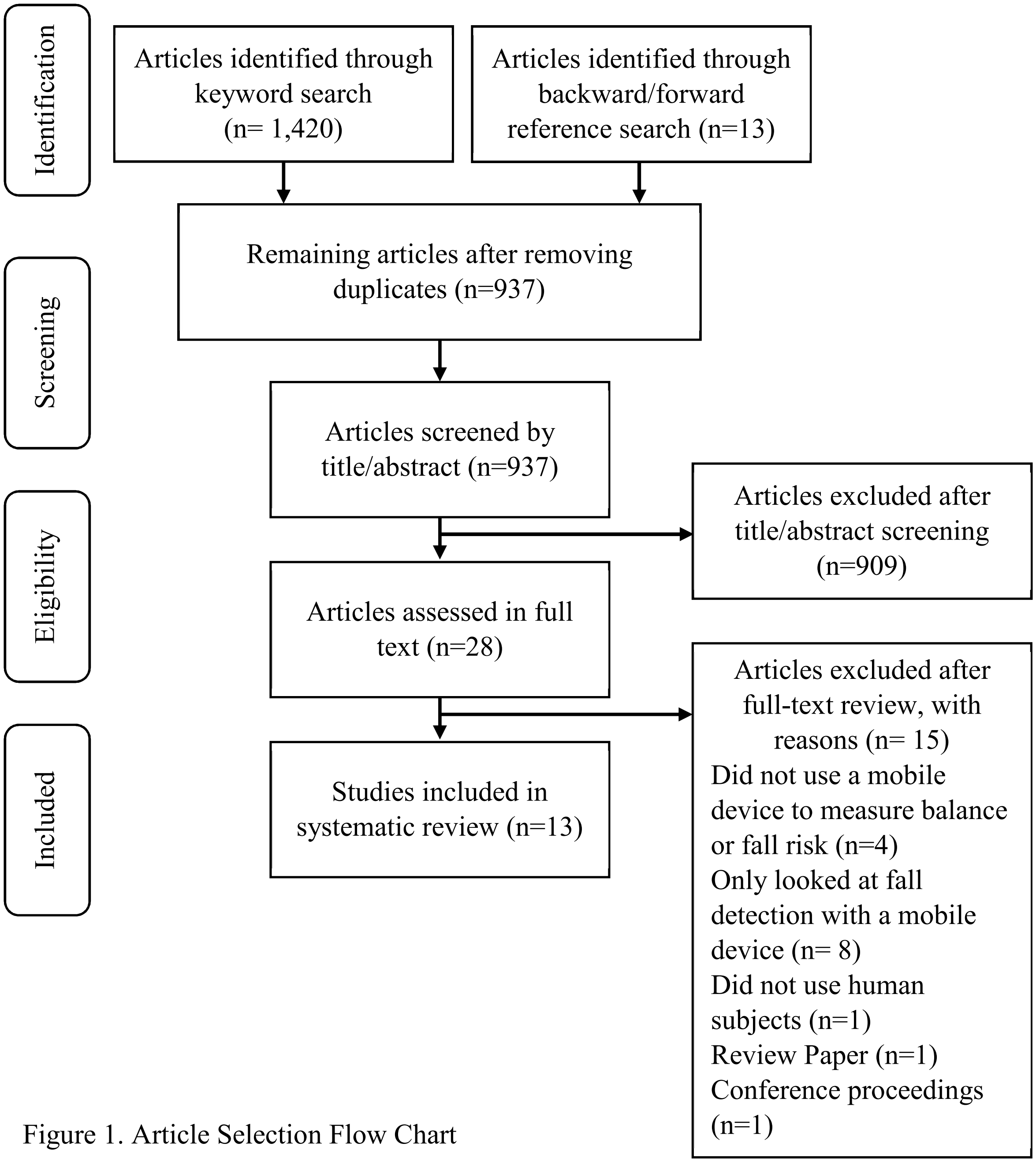



Figure 1. Article Selection Flow Chart

*1.3.2 Study Analysis*

Table 1 demonstrates the study characteristics for each article included in the review. All studies were cross sectional and included a sample of healthy individuals. Two studies included a sample of participants with Parkinson's disease, one group included a sample of frail individuals, and one study included individuals with vestibular dysfunction. Six studies included a sample of older adults (60+ years). Sample sizes ranged from 3-60 participants with five of the studies including ten individuals or less. Most studies were small and operated as feasibility studies for the application itself. Twelve of the 13 studies mentioned their applications could be used by a clinician. Seven of the 13 studies mentioned their applications were intended for patient use. Therefore, six of the studies mentioned their applications could be used by both clinicians and patients. Although these reports made mention of their intended user, they did not formally measure usability.

Table 1. Study Characteristics

| Author Name (Year) | Study Design | Population | Age (years) | Sample Size | Measures of Balance or Fall Risk | Main Outcome Measures | Measure of Validity | Measure of Reliability | Intended User |
|---|---|---|---|---|---|---|---|---|---|
| Fleury A. et al. (2013) | Cross sectional | Healthy | 62.7+/-2.7 | 6 | EC PL, EC TD | RMS and MPF | N/A | N/A | Patients |
| Madhushri P. et al (2016) | Cross sectional | Healthy | 28, 47, and 55 | 3 | TUG, 30s chair test, EO PL, EO ST, and EO SL | TUG: time, 30s chair test and static balance: angular velocity, displacement of the chest, change in trunk angle | N/A | N/A | Patients, caregivers, and clinicians |
| Wai A.A.P. et al. (2014) | Cross sectional | Healthy | Reported as: young adults | 5 | 9 items from the Berg | Sway area per second, mean distance, and mean velocity of sway | N/A | N/A | Patients and clinicians |
| Galán-Mercant A. and Cuesta-Vargas AI (2014) | Cross Sectional | Healthy and Frail | 82.78 | 18 | EO PL, EC PL, EO TD, and EC TD | Peak accelerations | N/A | N/A | Clinicians |
| Ozinga S.J., et al (2015) | Cross Sectional | Healthy and PD | Healthy: 62±10 and PD: 62±9 | Healthy: 17 and PD: 17 | EO PL, EC PL, EO TD, EO FS, EC FS, and EO TD FS | Peak to peak amplitude displacement, RMS, total power of acceleration signal, normalized path length, and 95% ellipsoid volume | Measured against 3D motion capture | N/A | Clinicians |
| Ozinga S.J. et al (2014) | Cross Sectional | Healthy | 68.3±6.9 | 12 | EO PL, EC PL, EO TD, EO FS, EC FS, and EO TD FS | Peak to peak amplitude displacement, RMS, total power of acceleration signal, normalized path length, and 95% ellipsoid volume | Measured against 3D motion capture | N/A | Clinicians |
| Milsoevic M. et al (2013) | Cross Sectional | Healthy and PD | Not reported | Healthy: 4 and PD: 3 | TUG | Total time, time to complete phases of the TUG, maximum change in trunk angle, maximum angular velocity | N/A | N/A | Patients and clinicians |

Table 1. (Cont.)

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Kosse N.M. et al. (2015) | Cross Sectional | Healthy (3 groups: YA, MA, and OA) | YA: 26±3.9, MA: 45±6.7, and OA: 65±5.5 | YA: 22, MA: 15, and OA: 23 | EO PL, EC PL, EO PL DT, EO TD, EC TD, and EO TD DT | RMS, mean sway area, median power of signal frequency, and total power of signal frequency | Measured against standalone accelerometer | ICC = 0.78-0.99 | Clinicians |
| Lee B.C. (2012) | Cross Sectional | Healthy and Vestibular Dysfunction | Healthy: 24±2.8, and Vestib: 42.3±13.5 | Healthy: 5 and Vestib: 5 | EO PL, EO ST, and EO TD | RMS, MPF, and elliptical area | N/A | N/A | Patients and clinicians |
| Franco C. et al. (2012) | Cross Sectional | Healthy | 26.5±3.7 | 20 | EC PL and EC TD | RMS and 95% spectral edge frequency | N/A | N/A | Patients and clinicians |
| Tacconi C. et al. (2011) | Cross Sectional | Not reported | Not reported | Not reported | TUG | RMS, total time, duration for separate elements, and max acceleration during sit to stand | N/A | N/A | Patients and clinicians |
| Cerrito A. et al. (2015) | Cross Sectional | Healthy | 73.5±10.4 | 16 | Sit to stand | Total time, peak force, rate of force development, and peak power | Measured against force platform | ICC = 0.43-.92 | Clinicians |
| Mellone S. et al. (2012) | Cross Sectional | Healthy | 59±16 | 49 | TUG | Total time, jerk (sit to stand), mean and SD of step time, and interstride trunk autocorrelation | Measured against standalone accelerometer | ICC = 0.42-0.96 | Clinicians |

Note: PD: Parkinson's disease, MA: middle-aged adults; EO: eyes open, EC: eyes closed, PL: feet parallel, ST: feet semi tandem, TD: feet tandem, FS: foam surface, DT: dual task, TUG: Timed-up-and-go Test; RMS: root mean square, MPF: mean power frequency; N/A: not applicable

Eight studies included measures of static balance, four studies included the TUG, one study included the Berg Balance Scale, one study included the 30s chair test, and one included the sit to stand test. Main outcome measures varied greatly from study to study. However, seven studies included RMS, five included some measure of sway area, and two included MPF for the static balance tests. For the TUG, all four studies report total time to complete and two studies also reported the time to complete individual elements (i.e. stand, walk, turn, etc.). The Berg Balance Scale was evaluated by sway area, mean distance, and mean velocity of sway of individual movement items. The 30s chair test was evaluated by angular velocity, displacement of the chest, and change in trunk angle. The sit to stand test used total time, jerk (sit to stand), and trunk movement measurements.

*1.3.3 Device Validity and Reliability*

Five of the 13 studies also evaluated the validity of their respective smartphone based measures by comparing to research grade measurement systems. For instance, in a series of investigations Alberts and colleagues utilized 3D motion capture and their iPad application to simultaneously measure movement during various movement tasks. Overall, the iPad application was significantly correlated with their 3D motion capture measurements (Ozinga & Alberts, 2014; Ozinga et al., 2015). Moreover, the iPad application was able to distinguish between the movement of PD patients and controls (Ozinga et al., 2015). Kosse N.M. et al. (2015) evaluated both gait and standing posture with an iPod Touch. Their application was also tested against standalone accelerometers to test for validity. The application was highly correlated (r=0.85-.99) to the outside measure of accelerometry. Mellone et al. (2012) had participants perform the TUG whilst simultaneously collecting data with their Android application and standalone accelerometer. However, the correlation coefficients were not reported, so validity is unclear.

Cerrito A. et al. (2015) tested their Android application against force platform measurements on a sit to stand test. The application measurements were strongly correlated with the force plate measures (r= 0.86–0.93). These studies all demonstrated the validity of their applications.

Only three of the 13 studies performed some measure of reliability. Kosse et al. (2015) evaluated test-retest reliability during eyes open parallel and eyes open semi-tandem stances. Both conditions demonstrated ICC values of 0.83-0.90 for RMS measures, ≥0.78 for MPF measures (except for MPF in the AP direction which had an ICC value of 0.59), and .81-.91 for sway area. Cerrito et al. (2015) evaluated relative reliability of the sit to stand test. Their mobile device produced ICC values of 0.91 for peak power, 0.92 for total time, 0.88 for max force, and 0.43 for rate of force development. Mellone et al. (2012) evaluated intra-rater reliability for the TUG test and found ICC values of 0.42-0.96 for eight different variables. Variables with ICC scores ≥0.75 were total duration, mean step time, and ML-interstride trunk autocorrelation.

**1.4 Literature Review**

This chapter systematically reviewed extant literature on mobile applications that evaluate dynamic and static balance. Studies were included if they measured static balance or a clinical measure of balance with a mobile device. Overall it is clear that although promising, smartphone balance applications are still in the development and initial testing phases. Sample sizes had a wide range and only a few studies included populations at risk for falls. Some evidence of validity was provided but questions about the applications reliability remain. A majority of the applications were intended for clinician use.

Only five of the 13 studies evaluated the validity of their applications. Standalone accelerometry, 3D motion capture, and force plate measurements were all used to test for validity. Of those, the results were promising and demonstrated strong concurrent validity. Even fewer studies, three out of the 13, included a measure of reliability. Although reliability measures were somewhat mixed several variables demonstrated high ICC values (≥0.75). The wide range of reliability estimates highlight the need to identify best metrics to be included as a measure of balance in mobile applications. Future studies should include measures of both validity and reliability when testing a new application.

All of the studies included in the current review were cross sectional. Further studies should also examine the applications ability to predict falls. This would increase the utility of such applications.

Given the increased likelihood of falls in older adults with disability, the inclusion of special populations with elevated fall risk would increase the scope of these apps. Only four of the 13 studies included clinical populations groups. The intended user is important to consider when designing these types of applications. Older adults and clinical populations are at a higher risk to experience perceptual and motor problems that would interfere with their ability to utilize the technology (Fisk, Rogers, Charness, Czaja, & Sharit, 2009). Furthermore, they might have cognitive deficits that hinder their ability to comprehend and remember instructions (Fisk et al., 2009). Therefore, in addition to measuring concurrent validity and reliability, applications should measure usability as well. None of the reviewed applications reported on usability. If an application is valid and reliable, it will be of little use if the intended population cannot properly operate it.

Despite the ubiquitous nature of mobile technology in society the use of it to measure balance and fall risk is relatively novel. The current review highlights the promise of this approach as well as the gaps in the literature. Future research needs to include measures of concurrent validity by comparing to gold standard methods as well as reliability analysis.

Additionally, applications should be designed with special consideration for the user's level of function and test for usability in those populations. The following chapter presents a study evaluating the validity of a smartphone based application on static balance in young and old adults.

# CHAPTER 2: Smartphone Based Balance Assessment

## 2.1 Purpose

The following investigation evaluates the validity and safety of a smartphone based application designed to measure standing balance in older adults. The application is intended for use by older adults as a fall risk screening tool. The application was validated against force platform posturography. It was hypothesized that the smartphone application would demonstrate strong concurrent validity by distinguishing between low fall risk and high fall risk older adults and correlating to the posturography data.

## 2.2 Methods

### *2.2.1 Participants*

This analysis consisted of a sample of 15 young adults, 13 low fall risk older adults, and 17 low fall risk older adults. To ensure participants had the cognitive ability to understand instructions, all were required to score greater than 20 on the Modified Telephone Interview for Cognitive Status (Knopman et al., 2010). To determine low and high fall risk in older adults, participants completed the short form of the physiological profile assessment (PPA) (Lord et al., 2003), a measure of physiological fall risk. The short form of the PPA consists of five tests examining vision, reaction time, proprioception, knee extensor strength, and standing balance. The results on these assessments are then combined together and compared to age and gender matched norms to calculate an individual z score. Larger values represent a higher fall risk score. A z score of zero indicates a normal fall risk for that individual's age and gender. The PPA has been validated as a predictor of falls in older adults (Lord et al., 2003). Older adults with a PPA score>0 were considered at a high risk of falling and those with a PPA score≤0 were considered at a low risk of falling.

*2.2.2 Procedures*

All testing procedures were approved by the local institutional review board. All measurements were collected during one visit to the research laboratory. Upon arriving at the research laboratory, participants were given a verbal explanation of the study, an informed consent document, and the ability to ask questions regarding the research study. After providing written informed consent, participants were asked to fill out a series of questionnaires and perform the standing balance test. All participants provided demographic information including age, gender, and number of falls in the previous year. A fall was defined as unintentionally coming to rest on the ground or a lower level.

Participants also completed the Activity-specific Balance Confidence (ABC) scale (Powell & Myers, 1995) to determine balance confidence during everyday activities. This 16-item measure asks participants to indicate their confidence performing an activity without losing their balance or becoming unsteady (e.g. 0% = no confidence, 100% = full confidence). An overall score on the ABC is calculated by averaging the 16 responses. A low ABC score indicates a subject is not confident in his/her ability to maintain balance during daily activities and puts them at a higher risk of falling (Lajoie & Gallagher, 2004). A high ABC score indicates a subject is very confident in his/her ability to maintain balance.

Participants also completed the Berg Balance Scale to evaluate a clinical measure of balance and fall risk (Bogle & Newton, 1996). The Berg uses 14 activities such as standing with feet together and picking up an object from the floor to evaluate balance and coordination. Items range from very simple (sitting with back unsupported) to challenging (standing on one foot). Each item is then scored from 0-4 based on performance. The final score is the sum of all 14 items and is out of a total of 56. Individuals in the 41-56 range are considered to have a low fall risk, individuals in the 21-40 range are considered to have a medium fall risk, and individuals in the 0-20 range are considered to have a high fall risk. Both the ABC scale and Berg Balance Scale have been shown to predict falls in older adults (Lajoie & Gallagher, 2004).

A smartphone usage questionnaire was used to determine participant smartphone use and interest in future balance applications. The questionnaire asked if they currently use a smartphone, use a tablet, use mobile health apps, and if they would consider using a smartphone powered balance application in the future. Smartphone and tablet use were yes/no response questions. The use of mobile health apps was answered on a five-option scale ranging from “yes, everyday” to “no, I have never used them.” Consideration for using a smartphone powered balance application in the future was answered on a four-option scale ranging from “yes, highly likely” to “no, I have no interest at all.”

During balance testing, adverse events were recorded to determine the application’s feasibility in a research setting. The total number of participant falls during testing were recorded. A fall was defined as unintentionally coming to rest on the ground or lower level. At all times participants were supervised by trained research personnel to help reduce the risk of falling.

Static balance was measured with a progressive series of seven balance tests. Each test was performed twice for 30 seconds: eyes open single task, eyes closed single task, eyes open with a dual task, eyes closed with a dual task, semi-tandem stance, tandem stance, and a single leg stance. These tests were used due to their previous ability to predict falls and in older adults (Piirtola & Era, 2006; Vellas et al., 1997). The dual task was serial subtractions by sevens with a new starting stimulus for each trial.

*2.2.3 Testing Equipment*

Figure 2 depicts the experimental set up. Participants' balance was assessed with a Bertec force platform (Bertec Corporation, Columbus, OH) and a Samsung Galaxy S6 (Samsung, Seoul, South Korea) smartphone. The force platform is the gold standard for measuring balance impairment and was used to help validate the smartphone application (Raymakers, Samson, & Verhaar, 2005).

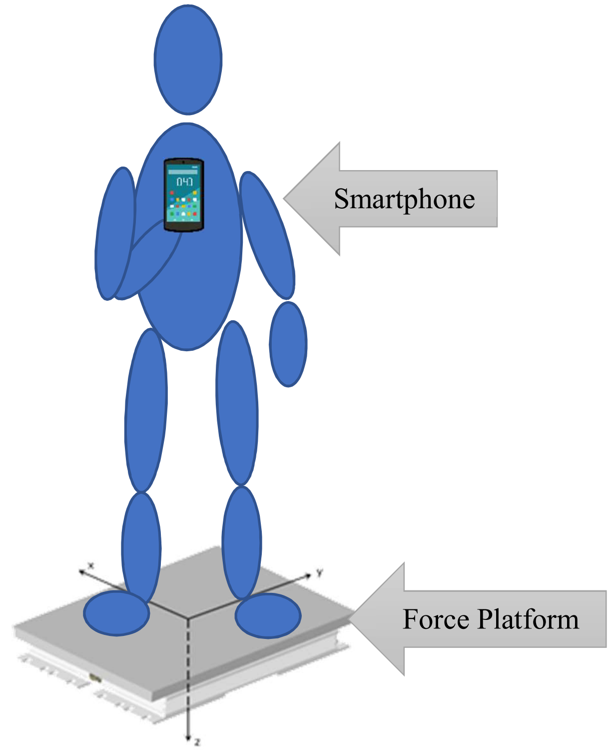


Figure 2. Participant set up

Posturographic analysis was based on the motion of the center of pressure (COP) as calculated by the force plate (Raymakers et al., 2005). The force platform simultaneously measures force and moment components in the anteroposterior (AP), mediolateral (ML), and vertical axes which can be combined to provide the COP location throughout the measurement period. Custom MATLAB (Mathworks Inc., Natick, MA) code was used to calculate all measures. Measures including mean velocity along the mediolateral (MVML) axis, mean velocity along the anteroposterior (MVAP) axis, mean radial velocity (MVRAD), and the 95% area confidence ellipse (CE). These measures were chosen due to their ability to predict falls and recurrent falls in older adults (Piirtola & Era, 2006). Measures were averaged across the two trials for each participant.

Participants held the smartphone in their dominant hand medially against their chest along their sternum. The phone was held against their chest for the duration of the 30 seconds for each test. Participants were instructed not to move the phone once in place for testing. The phone produced a series of six beeps to countdown the start of the trial. The phone then beeped at the end of the 30 second trial to indicate the test was over. All participants performed a practice trial to ensure understanding of the operations. The Samsung Galaxy S6 is equipped to measure accelerations in three dimensions.

A novel app was developed to enable the collection and storage of the accelerometer sensor output of the phone during balance trials. For each testing condition, the acceleration data was stored to a csv file local to the phone and later transferred to a computer for post processing after completion of the testing session. A custom MATLAB script was created to import and perform calculations on the acceleration data. For each testing condition, maximal acceleration along the X, Y, and Z axes as well as the root mean square of the total signal duration along the X, Y, and Z axes were calculated. The root mean square provides an indication of average magnitude of a signal regardless of sign and is useful when quantifying signals that oscillate between positive and negative values such as accelerometry during balance (O'Sullivan, Blake, Cunningham, Boyle, & Finucane, 2009).

*2.2.4 Statistical Analyses*

Mean, standard deviation, and range were determined for age, posturographic, and smartphone measures. Median and interquartile range were determined for number of falls in the previous year. Independent samples t-tests and chi-squared tests were used to determine difference in age and gender respectively between the older adult groups. Proportions of failures (unable to complete a task) was determined for each group and balance condition. A Wald chi-square test for independence was used to evaluate differences in failure rates with group (low fall risk older adults and high fall risk older adults) as the between subject factor and balance condition (tandem stance and single leg stance) as the within subject factor. The young adult group was not included in the analysis as no failures were reported for any balance condition. The tandem and single leg conditions were used due to their non-zero failure rates (i.e. some participants were unable to complete conditions) in the older adult groups.

The Shapiro-Wilk test was utilized to examine the normality of the outcome measures. One-way ANOVAs were used to determine differences between groups on fall risk measures (ABC score, the Berg Balance Scale, and PPA). Differences between groups on force plate measures and smartphone measures were analyzed using mixed-model 3x7 repeated-measures ANOVAs with group (young adult, low fall risk older adult, and high fall risk older adult) as the between subject factor and condition (eyes open single task, eyes closed single task, eyes open dual task, eyes closed dual task, semi-tandem, tandem, and single leg) as the within subject factor. Participants were only included in analysis if they successfully completed the balance condition. All participants were able to complete conditions of eyes open single task, eyes closed single task, eyes open dual task, eyes closed dual task, and semi-tandem, therefore, additional mixed-model 3x5 repeated-measures ANOVAs with group (young adult, low fall risk older adult, and high fall risk older adult) as the within subject factors and condition (eyes open single task, eyes closed single task, eyes open dual task, eyes closed dual task, and semi-tandem) were done to analyze differences on force platform and smartphone measures. The relationships between force plate measurements and smartphone measurements were examined with Spearman Rank-Order correlations. All levels of statistical significance were set at $p \leq .05$. All statistical analyses were performed in SPSS version 22 (IBM Inc., Armonk, NY).

## 2.3 Results

### *2.3.1 Demographics and Fall Risk*

The sample included 45 individuals. Fifteen young adults participated, 13 low fall risk older adults participated, and 17 high fall risk older adults participated. The young adult group consisted of eight males and seven females with an average age of 21.9±2.8 years. The low fall risk older adult group consisted of six males and seven females with an average age of 65.0±5.0 years. The high fall risk older adult group consisted of six males and 11 females with an average age of 68.8±6.4 years. The low fall risk older adult group was similar in age to the high fall risk older adult group [$t(28)=-1.7$, $p=.504$]. The low fall risk older adult group was similar in gender to the high fall risk older adult group ($\chi^2=.36$, $p=.547$). Table 2 presents fall risk information.

Table 2. Fall Risk Information

| | YA | LFR | HFR |
|---|---|---|---|
| ABC Score* | 97.3%±6.5% | 91.3%±9.8% | 88.5%±11.3% |
| Berg Balance Score* | 56±0 | 55.9±.28 | 54.1±3.3 |
| PPA (z-score)* | -.95±.61 | -.50±.36 | 1.41±.81 |
| Falls in One Year | 0(0-0) | 0(0-1) | 1(0-1) |

Note: ABC score, Berg Balance Score, and PPA are presented as mean±SD, Falls in One Year are presented as median(IQR); YA=young adults, LFR=low fall risk older adults, HFR=high fall risk older adults; ABC=Activities Specific Balance Confidence Score, PPA=Physiological Profile Assessment; * indicates significant group effect ($p\leq.05$)

Statistically significant group effects were seen for ABC scores [$F(2)=3.8$, $p\leq.05$], the Berg Balance Scale [$F(2)=4.5$, $p\leq.05$], and PPA scores [$F(2)=60.2$, $p\leq.01$]. Post-hoc analysis revealed low fall risk older adults and high fall risk older adults were not significantly different on the ABC scale ($p=.408$). However, the low fall risk older adult group was significantly different from the high fall risk older adult group on the Berg Balance Scale and PPA ($p<.05$). No adverse events, falls, were recorded in any groups during the entirety of the testing. The smartphone usage questionnaire results are reported in table 3.

Table 3. Smartphone Usage Questionnaire

| | Response Selection | Young Adults N | Young Adults % | Low Fall Risk Older Adults N | Low Fall Risk Older Adults % | High Fall Risk Older Adults N | High Fall Risk Older Adults % |
|---|---|---|---|---|---|---|---|
| | Yes, I use a smartphone | 15 | 100 | 12 | 92 | 14 | 82 |
| | Yes, I use a tablet | 1 | 7 | 6 | 46 | 10 | 59 |
| Q1 | Yes, Everyday | 6 | 40 | 4 | 31 | 4 | 24 |
| | Yes, Weekly | 3 | 20 | 1 | 8 | 2 | 12 |
| | Yes, Monthly | 0 | 0 | 0 | 0 | 0 | 0 |
| | No, But I have in the past | 3 | 20 | 0 | 0 | 1 | 6 |
| | No, I have never used them | 2 | 13 | 8 | 62 | 10 | 59 |
| Q2 | Yes, Highly likely | 0 | 0 | 4 | 31 | 2 | 12 |
| | Yes, I would try it out | 6 | 40 | 4 | 31 | 12 | 71 |
| | Probably not, but I might consider it | 7 | 47 | 3 | 23 | 0 | 0 |
| | No, I have no interest at all | 2 | 13 | 2 | 15 | 3 | 18 |

Note: Q1: Do you currently use mobile health apps?, Q2: Would you consider using a smartphone powered balance app in the future?

Two participants (15%) in the low fall risk older adult group were unable to complete the single leg condition and one (8%) was unable to complete the tandem condition. Within the high fall risk older adult group, eight participants (47%) were unable to complete the single leg condition and five participants (29%) were unable to complete the tandem condition. All participants were able to complete the eyes open single task, eyes closed single task, eyes open dual task, eyes closed dual task, and semi-tandem conditions. Failure rates were different between groups (Wald $\chi^2$=4.0, $p$<.05). There was no effect of task or a group by task interaction ($p$>.05) on failure rates.

*2.3.2 Force platform*

Descriptive statistics for force platform data are reported in table 4.

Table 4. Descriptive Statistics: Force Platform

| | Variable | Young Adults Mean | Young Adults Range | Low Fall Risk Older Adults Mean | Low Fall Risk Older Adults Range | High Fall Risk Older Adults Mean | High Fall Risk Older Adults Range |
|---|---|---|---|---|---|---|---|
| EOST | MVAP | 4.8±0.9 | 3.2-7.0 | 8.2±2.0 | 4.8-12.4 | 11.9±8.0 | 4.6-29.6 |
| | MVML* | 2.8±0.9 | 1.7-4.1 | 3.4±0.9 | 2.5-6.3 | 4.4±2.4 | 2.2-10.5 |
| | MVRAD | 6.1±1.3 | 4.0-8.9 | 9.5±2.0 | 6.3-13.1 | 13.5±8.5 | 5.5-32.3 |
| | CEA* | 86.1±42.2 | 33.4-116.3 | 150.7±91.3 | 42.1-311.2 | 192.8±128.2 | 57.3-460.1 |
| ECST | MVAP | 7.4±2.3 | 4.8-11.9 | 11.3±3.2 | 5.7-15.9 | 19.1±16.5 | 4.8-56.6 |
| | MVML* | 4.2±2.4 | 1.7-11.3 | 4.3±1.3 | 2.5-7.7 | 6.2±4.3 | 2.1-15.8 |
| | MVRAD | 9.5±3.7 | 5.3-19.5 | 12.9±3.4 | 7.4-18.6 | 21.2±17.6 | 6.1-61.6 |
| | CEA* | 223.2±400.8 | 53.3-1642.4 | 151.3±63.2 | 68.9-279.2 | 363.5±275.8 | 88.3-972.7 |
| EODT | MVAP | 6.0±2.0 | 2.5-10.7 | 10.1±3.1 | 6.3-17.6 | 13.9±8.6 | 5.6-37.3 |
| | MVML* | 3.4±1.4 | 1.9-7.2 | 5.6±4.3 | 2.6-18.1 | 6.0±3.7 | 2.6-17.8 |
| | MVRAD | 7.5±2.5 | 3.7-12.9 | 12.7±5.5 | 7.5-28.6 | 16.5±9.4 | 6.7-39.1 |
| | CEA* | 92.9±47.2 | 37.8-213.9 | 274.7±466.8 | 53.4-1801.8 | 565.0 ±1138.2 | 35.1-4919.3 |
| ECDT | MVAP | 8.9±2.8 | 5.3-14.2 | 12.4±4.3 | 5.0-19.0 | 19.2±16.9 | 6.2-64.6 |
| | MVML* | 3.9±1.2 | 2.4-6.1 | 6.0±4.4 | 3.0-19.8 | 7.8±9.3 | 2.7-41.9 |
| | MVRAD | 10.5±3.0 | 6.4-16.6 | 15.1±6.3 | 7.2-31.7 | 22.3±19.6 | 7.3-66.9 |
| | CEA* | 182.1±119.0 | 56.8-496.0 | 275.9±448.5 | 63.7-1759.1 | 1733.7 ±5942.2 | 46.9-24778.9 |
| ST | MVAP | 11.1±2.8 | 7.1-15.5 | 15.8±5.4 | 9.0-29.8 | 19.5±13.8 | 7.7-54.9 |
| | MVML* | 9.2±2.3 | 6.1-14.0 | 14.9±3.5 | 10.9-22.0 | 19.0±10.5 | 8.4-45.6 |
| | MVRAD | 15.9±3.9 | 10.4-23.0 | 24.0±6.1 | 16.5-36.5 | 29.9±18.8 | 12.6-71.4 |
| | CEA* | 321.4±169.9 | 144.6-703.9 | 425.8±278.1 | 172.7-1127.8 | 731.4±444.9 | 166.5-1638.3 |
| Tandem | MVAP | 17.1±5.7 | 8.3-28.3 | 31.4±17.4 | 9.9-73.5 | 25.6±9.8 | 12.0-43.3 |
| | MVML* | 15.2±4.2 | 7.6-23.0 | 29.7±11.6 | 16.7-55.9 | 25.5±7.8 | 15.0-39.4 |
| | MVRAD | 25.2±7.5 | 13.9-39.2 | 48.2±21.7 | 21.3-91.1 | 40.0±12.7 | 21.3-60.3 |
| | CEA* | 560.8±237.3 | 242.2-940.1 | 1394.4 ±2178.7 | 312.9-8223.6 | 1166.2 ±601.7 | 267.8-2119.0 |
| SL | MVAP | 20.6±7.5 | 12.1-41.1 | 40.3±22.7 | 3.7-79.1 | 31.9±9.7 | 16.7-51.1 |
| | MVML* | 21.3±8.6 | 12.6-48.4 | 40.1±16.2 | 6.2-58.1 | 39.1±19.0 | 23.9-87.9 |
| | MVRAD | 32.9±12.6 | 20.9-71.6 | 63.4±30.6 | 7.4-109.6 | 55.7±22.6 | 31.9-112.7 |
| | CEA* | 841.5±880.6 | 193.0-3741.3 | 3945.2 ±7402.7 | 428.9-25681.9 | 4866.5 ±12169.6 | 497.2-39469.5 |

Note: Mean±SD, Range reported as min-max; MVAP, MVML, and MVRAD reported in mm/s$^2$, CEA reported in mm; EOST: eyes open single task, ECST: eyes closed single task, EODT: eyes open dual task, ECDT: eyes closed dual task, ST: semi-tandem, SL: single leg; * indicates significant group by condition interaction on the 3x5 ANOVA

Repeated measures ANOVAs revealed significant group effect for MVAP, MVML, and MVRAD variables when including all seven balance conditions. There was not a significant group effect for CEA on all seven standing balance conditions. Statistics and pairwise comparisons are reported in table 5.

Table 5. Force Platform Group Effect Statistics on Seven Balance Conditions

| | | | Pairwise Comparison | | |
|---|---|---|---|---|---|
| Measure | F | *p* | *p* YA vs LFR | *p* YA vs LFR | *p* HFR vs LFR |
| MVAP | 7.4 | .002* | .001* | .017* | .304 |
| MVML | 8.9 | .001* | .001* | .002* | .805 |
| MVRAD | 8.7 | .001* | .001* | .005* | .457 |
| CEA | 2.4 | .110 | -- | -- | -- |

Note: balance conditions include eyes open single task, eyes closed single task, eyes open dual task, eyes closed dual task, semi-tandem, tandem, and single leg; * statistical significance ($p \leq .05$); YA: young adults, LFR: low fall risk older adults, HFR: high fall risk older adults

Repeated measures ANOVAs revealed significant group effect for MVAP, MVML, and MVRAD variables when only including the five balance conditions all participants were able to complete (eyes open single task, eyes closed single task, eyes open dual task, eyes closed dual task, and semi-tandem conditions). There was not a significant group effect for CEA in these five balance conditions. Statistics and pairwise comparisons are reported in table 6.

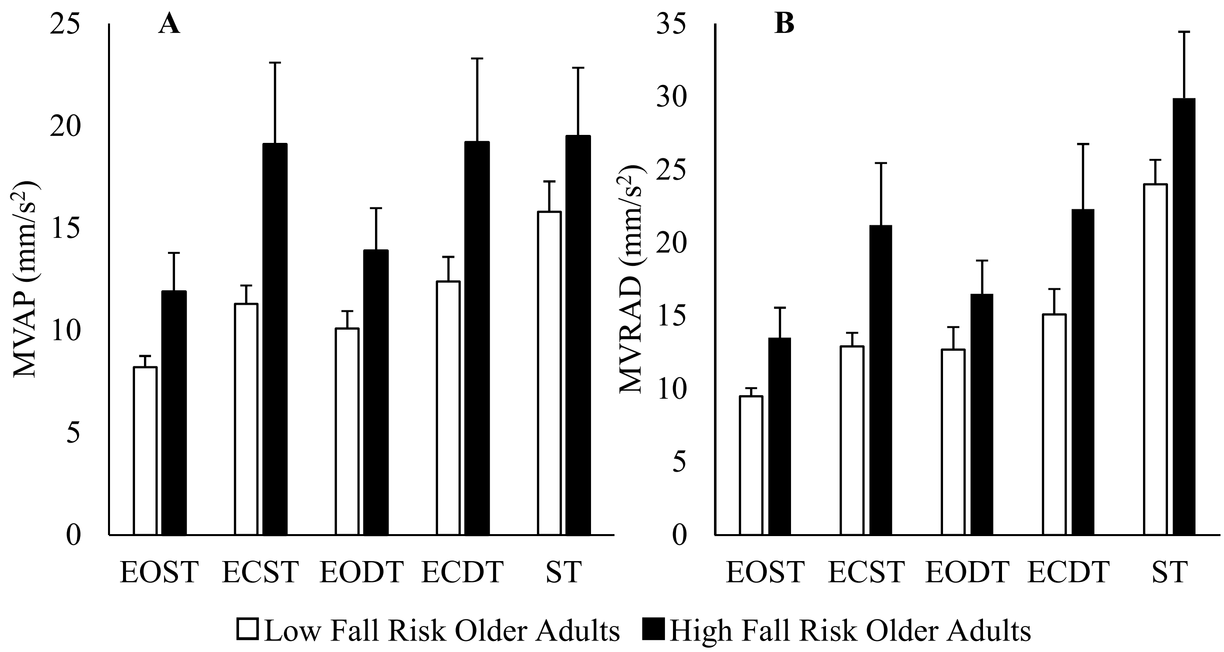
Table 6. Force Platform Group Effect Statistics on Five Balance Conditions

| | | | Pairwise Comparison | | |
|---|---|---|---|---|---|
| Measure | F | *p* | *p* YA vs LFR | *p* YA vs HFR | *p* LFR vs HFR |
| MVAP | 6.8 | .003* | .148 | .001* | .052* |
| MVML | 7.5 | .002* | .060 | .000* | .092 |
| MVRAD | 7.3 | .002* | .112 | .000 | .054* |
| CEA | 1.6 | .207 | -- | -- | -- |

Note: balance conditions include eyes open single task, eyes closed single task, eyes open dual task, eyes closed dual task, and semi-tandem; * statistical significance ($p \leq .05$); YA: young adults, LFR: low fall risk older adults, HFR: high fall risk older adults

Force platform variables that were able to distinguish between low fall risk older adults and high fall risk older adults (MVAP and MVRAD) are displayed in figure 3.

Figure 3. Force Platform Measures as a Function of Group and Balance Condition




Note: 3. A depicts mean velocity in the AP direction, 3. B depicts mean radial velocity; EOST: eyes open single task, ECST: eyes closed single task, EODT: eyes open dual task, ECDT: eyes closed dual task, ST: semi-tandem; Standard Error bars are shown for each group and condition

*2.3.3 Smartphone Metrics*

Descriptive Statistics for smartphone measures are reported in table 7.

Table 7. Descriptive Statistics: Smartphone

| | Variable | Young Adults Mean | Young Adults Range | Low Fall Risk Older Adults Mean | Low Fall Risk Older Adults Range | High Fall Risk Older Adults Mean | High Fall Risk Older Adults Range |
|---|---|---|---|---|---|---|---|
| EOST | Max X | 0.30±0.13 | 0.15-0.61 | 1.08±1.93 | 0.16-6.18 | 0.31±0.18 | 0.14-0.86 |
| | Max Y | 10.02±0.07 | 9.95-10.19 | 10.35±0.84 | 9.92-12.95 | 10.05±0.12 | 9.93-10.36 |
| | Max Z | 1.34±0.25 | 0.99-2.02 | 2.52±2.65 | 0.96-8.54 | 1.35±0.36 | 0.99-2.60 |
| | RMS X | 0.07±0.02 | 0.04-0.11 | 0.09±0.06 | 0.04-0.24 | 0.07±0.03 | 0.04-0.16 |
| | RMS Y | 9.81±0.00 | 9.81-9.81 | 9.81±0.00 | 9.81-9.81 | 9.81±0.00 | 9.81-9.81 |
| | RMS Z | 0.14±0.01 | 0.11-0.16 | 0.24±0.23 | 0.11-0.89 | 0.16±0.04 | 0.11-0.27 |
| ECST | Max X | 0.36±0.21 | 0.16-0.93 | 0.49±0.94 | 0.15-3.61 | 0.34±0.21 | 0.12-0.83 |
| | Max Y | 10.06±0.10 | 9.95-10.30 | 10.01±0.17 | 9.93-10.55 | 10.08±0.15 | 9.94-10.46 |
| | Max Z | 1.37±0.21 | 0.93-1.74 | 1.90±2.39 | 0.99-9.85 | 1.38±0.38 | 0.67-2.57 |
| | RMS X | 0.08±0.03 | 0.04-0.12 | 0.07±0.05 | 0.04-0.24 | 0.07±0.03 | 0.03-0.15 |
| | RMS Y | 9.81±0.00 | 9.81-9.81 | 9.81±0.00 | 9.81-9.81 | 9.81±0.00 | 9.81-9.81 |
| | RMS Z | 0.15±0.02 | 0.11-0.18 | 0.19±0.21 | 0.11-0.88 | 0.17±0.05 | 0.12-0.30 |
| EODT | Max X | 0.40±0.13 | 0.17-0.57 | 1.06±2.48 | 0.19-9.30 | 0.43±0.22 | 0.16-1.00 |
| | Max Y | 10.13±0.09 | 9.96-10.29 | 10.19±0.28 | 9.96-11.06 | 10.16±0.13 | 9.97-10.49 |
| | Max Z | 1.36±0.21 | 0.88-1.64 | 2.65±4.79 | 0.95-18.57 | 1.48±0.88 | 0.69-4.61 |
| | RMS X | 0.09±0.03 | 0.05-0.14 | 0.14±0.18 | 0.04-0.70 | 0.10±0.04 | 0.05-0.23 |
| | RMS Y | 9.81±0.00 | 9.81-9.81 | 9.81±0.00 | 9.81-9.82 | 9.81±0.00 | 9.81-9.81 |
| | RMS Z | 0.16±0.03 | 0.11-0.21 | 0.29±0.44 | 0.13-1.76 | 0.19±0.07 | 0.13-0.43 |
| ECDT | Max X | 0.47±0.31 | 0.14-1.46 | 1.39±3.68 | 0.25-13.62 | 0.42±0.15 | 0.19-0.70 |
| | Max Y | 10.16±0.18 | 9.96-10.65 | 10.26±0.53 | 9.99-12.00 | 10.20±0.27 | 9.95-11.15 |
| | Max Z | 1.39±0.26 | 0.97-1.71 | 2.79±5.02 | 1.05-19.48 | 1.36±0.21 | 0.86-1.82 |
| | RMS X | 0.09±0.05 | 0.04-0.21 | 0.15±0.19 | 0.05-0.78 | 0.10±0.04 | 0.05-0.16 |
| | RMS Y | 9.81±0.00 | 9.81-9.81 | 9.81±0.00 | 9.81-9.82 | 9.81±0.00 | 9.81-9.81 |
| | RMS Z | 0.19±0.05 | 0.12-0.29 | 0.32±0.48 | 0.12-1.89 | 0.18±0.04 | 0.13-0.32 |
| ST | Max X | 0.40±0.15 | 0.22-0.78 | 1.17±3.09 | 0.18-11.45 | 0.41±0.27 | 0.20-1.38 |
| | Max Y | 10.09±0.15 | 9.94-10.56 | 10.22±0.77 | 9.95-12.79 | 10.11±0.17 | 9.95-10.63 |
| | Max Z | 1.24±0.19 | 0.87-1.50 | 2.55±4.98 | 0.76-19.10 | 1.31±0.23 | 0.96-1.90 |
| | RMS X | 0.10±0.03 | 0.06-0.15 | 0.12±0.13 | 0.06-0.54 | 0.11±0.06 | 0.06-0.35 |
| | RMS Y | 9.81±0.00 | 9.81-9.81 | 9.81±0.01 | 9.81-9.83 | 9.81±0.00 | 9.81-9.81 |
| | RMS Z | 0.15±0.02 | 0.11-0.18 | 0.28±0.47 | 0.12-1.84 | 0.18±0.06 | 0.12-0.33 |
| Tandem | Max X | 0.46±0.09 | 0.28-0.67 | 0.93±1.10 | 0.27-4.34 | 0.56±0.40 | 0.27-1.71 |
| | Max Y | 10.18±0.10 | 10.02-10.37 | 10.46±0.36 | 10.01-11.18 | 10.25±0.19 | 10.01-10.57 |
| | Max Z | 1.32±0.19 | 1.03-1.64 | 2.30±3.59 | 0.97-13.69 | 1.25±0.23 | 0.79-1.71 |
| | RMS X | 0.11±0.03 | 0.08-0.18 | 0.18±0.09 | 0.07-0.41 | 0.16±0.09 | 0.07-0.40 |
| | RMS Y | 9.81±0.00 | 9.81-9.81 | 9.81±0.00 | 9.81-9.81 | 9.81±0.00 | 9.81-9.81 |
| | RMS Z | 0.16±0.02 | 0.12-0.22 | 0.27±0.33 | 0.13-1.32 | 0.21±0.07 | 0.12-0.34 |
| SL | Max X | 0.55±0.24 | 0.33-1.11 | 2.65±3.55 | 0.41-12.18 | 0.77±0.48 | 0.27-1.56 |
| | Max Y | 10.43±0.37 | 10.15-11.29 | 11.43±1.71 | 10.19-15.68 | 10.39±0.26 | 10.08-10.83 |
| | Max Z | 1.42±0.24 | 1.12-2.04 | 6.39±10.15 | 1.23-34.61 | 1.14±0.26 | 0.57-1.52 |
| | RMS X | 0.15±0.07 | 0.10-0.30 | 0.52±0.60 | 0.14-1.95 | 0.19±0.08 | 0.09-0.32 |
| | RMS Y | 9.81±0.00 | 9.81-9.81 | 9.89±0.26 | 9.81-10.67 | 9.81±0.00 | 9.81-9.81 |
| | RMS Z | 0.20±0.06 | 0.14-0.31 | 0.92±1.67 | 0.17-5.80 | 0.23±0.08 | 0.14-0.38 |

Note: Mean reported as Mean±SD, Range reported as min-max; Values are reported in $m/s^{2;}$ EOST: eyes open single task, ECST: eyes closed single task, EODT: eyes open dual task, ECDT:

eyes closed dual task, ST: semi-tandem, SL: single leg; * indicates significant group by condition interaction on the 3x5 ANOVA

Repeated measures ANOVAs revealed significant group effect for Max Acceleration Y and RMS X variables when including all seven balance conditions. There was not a significant group effect for Max Acceleration X, Max Acceleration Z, RMS Y, and RMS Z on all seven standing balance conditions. Statistics and pairwise comparisons are reported in table 8.

Table 8. Smartphone Group Effect Statistics on Seven Balance Conditions

| | | | Pairwise Comparison | | |
|---|---|---|---|---|---|
| Measure | F | *p* | *p* YA vs LFR | *p* YA vs HFR | *p* LFR vs HFR |
| Max Accel X | 2.7 | .074 | -- | -- | -- |
| Max Accel Y | 4.6 | .024* | .013* | .900 | .020* |
| Max Accel Z | 2.5 | .075 | -- | --- | -- |
| RMS X | 4.2 | .025* | .012* | .954 | .026* |
| RMS Y | 1.4 | .239 | -- | -- | -- |
| RMS Z | 2.8 | .058 | -- | -- | -- |

Note: balance conditions include eyes open single task, eyes closed single task, eyes open dual task, eyes closed dual task, semi-tandem, tandem, and single leg; * statistical significance ($p \leq .05$); YA: young adults, LFR: low fall risk older adults, HFR: high fall risk older adults

Repeated measures ANOVAs revealed no significant group effects or group by condition effects ($p > .05$) for smartphone measurements when considering five balance conditions that all participants completed (eyes open single task, eyes closed single task, eyes open dual task, eyes closed dual task, and semi-tandem conditions).

*2.3.4 Correlation Statistics – Concurrent Validity*

Spearman rank-order correlations were used due to the non-normality of the force platform and smartphone data. Significant correlations ($p \leq .05$) were found in all conditions (eyes open single task, eyes closed single task, eyes open dual task, eyes closed dual task, semi-tandem, tandem, and single leg). Correlation coefficients (Spearman's rho) are report in table 9.

Table 9. Spearman Rank-Order Correlations: Spearman Rho Values

| | Variable | MVAP | MVML | MVRAD | CEA |
|---|---|---|---|---|---|
| EOST | Max X | .300* | .360* | .310* | 0.139 |
| | Max Y | .341* | .298* | .329* | .375* |
| | Max Z | 0.017 | 0.028 | 0.032 | -0.074 |
| | RMS X | 0.168 | 0.274 | 0.185 | 0.18 |
| | RMS Y | 0.194 | 0.129 | 0.18 | 0.143 |
| | RMS Z | .319* | 0.155 | .311* | 0.212 |
| ECST | Max X | 0.199 | .415** | 0.273 | 0.177 |
| | Max Y | 0.15 | .312* | 0.213 | 0.225 |
| | Max Z | -0.074 | 0.225 | 0.014 | -0.012 |
| | RMS X | 0.204 | .408** | 0.275 | 0.244 |
| | RMS Y | 0.291 | 0.281 | .315* | 0.264 |
| | RMS Z | .393** | .587** | .482** | .402** |
| EODT | Max X | 0.152 | 0.29 | 0.204 | 0.044 |
| | Max Y | 0.19 | 0.21 | 0.201 | 0.062 |
| | Max Z | -0.236 | -0.233 | -0.243 | -0.211 |
| | RMS X | 0.262 | .322* | .296* | 0.233 |
| | RMS Y | .362* | .438** | .379* | .312* |
| | RMS Z | .440** | .516** | .472** | .400** |
| ECDT | Max X | 0.015 | .417** | 0.116 | 0.048 |
| | Max Y | 0.049 | .362* | 0.137 | 0.137 |
| | Max Z | 0.044 | 0.061 | 0.035 | -0.055 |
| | RMS X | 0.08 | .391** | 0.138 | 0.115 |
| | RMS Y | 0.142 | .390** | 0.21 | 0.249 |
| | RMS Z | .304* | .504** | .365* | 0.257 |
| ST | Max X | .376* | 0.256 | .312* | 0.269 |
| | Max Y | .396** | 0.285 | .324* | .466** |
| | Max Z | 0.16 | 0.141 | 0.159 | 0.013 |
| | RMS X | .471** | .394** | .421** | .529** |
| | RMS Y | .430** | .427** | .417** | .663** |
| | RMS Z | .351* | .451** | .399** | .709** |
| Tandem | Max X | .509** | .336* | .429** | .438** |
| | Max Y | .745** | .597** | .704** | .593** |
| | Max Z | 0.103 | -0.073 | 0.033 | -0.165 |
| | RMS X | .705** | .583** | .675** | .620** |
| | RMS Y | .791** | .644** | .757** | .709** |
| | RMS Z | .658** | .469** | .596** | .620** |
| SL | Max X | .592** | .587** | .600** | .614** |
| | Max Y | .623** | .572** | .602** | .525** |
| | Max Z | .348* | 0.27 | 0.314 | 0.221 |
| | RMS X | .618** | .631** | .637** | .662** |
| | RMS Y | .757** | .692** | .733** | .529** |
| | RMS Z | .625** | .661** | .661** | .602** |

Note (tables 9-15): *indicates significance at $p \leq .05$, **indicates significance at $p \leq .01$; N=45 for eyes open single task, eyes closed single task, eyes open dual task, eyes closed dual task, and semi-tandem, N=39 for tandem, and N=35 for single leg

## CHAPTER 3: Discussion

This thesis includes a cross-sectional study evaluating a novel smartphone application that measures balance impairment under several static balance conditions. The application was successfully tested in a group of healthy young adults, low fall risk older adults, and high fall risk older adults. The application was also tested simultaneously with a force platform, the gold standard of posturography, to examine concurrent validity.

As identified in the systematic review above, although there have been numerous reports of mobile health applications assessing balance, there is a general lack of reporting on concurrent validity. This investigation fills that gap. The main findings from the study include several correlations between the force platform measures and smartphone measures. Spearman rank-order correlations demonstrated 32 moderate correlations ($.5 \leq \rho \leq .7$) and 9 strong correlations ($\rho \geq .7$) out of 168 total force platform and smartphone measure combinations. Of the six smartphone measures, RMS Z was significantly correlated to the posturographic measures on 25 out of the 28 possible occurrences. Overall, these observations suggest the smartphone application as tested is a valid measure of standing balance.

Overall, these results are similar to the few studies that have included measures of validity. For example, Alberts and colleagues demonstrated significant correlations between their iPad application and a standalone 3D motion capture system. Their application was also able to distinguished between controls and PD patients (Ozinga & Alberts, 2014; Ozinga et al., 2015). Kosse et al. (2015) used an iPod touch application and demonstrated correlations between their application and a standalone accelerometer. Both the iPad and iPod touch were used to evaluate standing balance. Cerrito et al. (2015) tested an android application against a force platform during a sit to stand test. Similar to this study, their android application measures were strongly correlate to the force plate measures.

Posturographic measures (mean velocity in the AP direction and mean radial velocity) are considered the gold standard in quantify standing balance in older adults (Raymakers et al., 2005). As expected, they were able to distinguish between older adults with low fall risk older adults and high fall risk when examining the five balance tests all participants were able to complete. Similarly, smartphone measures (max acceleration Y and root mean square X) were able to distinguish between low fall risk and high fall risk older adults. However, the results are inconclusive as some balance conditions demonstrated higher impairment in the low fall risk group.

Not surprisingly most of the participants who were unable to complete tests came from the high fall risk older adult group. Within the high fall risk older adult group, 47% were unable to complete the single leg condition and 29% were unable to complete the tandem condition. Interestingly, participants in the high fall risk older adult group who were unable to complete the tandem condition had a mean PPA z score of 1.87±.87 and those unable to complete the single leg condition had a mean PPA z score of 1.50±1.0. Both values are higher than the overall group mean PPA score of 1.41±.81. In the low fall risk older adults group, only 15% were unable to complete the single leg condition and 8% were unable to complete the tandem condition. Future iterations of the smartphone application may want to collect unwillingness or inability to complete challenging balance tasks as a proxy for balance confidence.

Moreover, failure rates (i.e. unable to complete a task) were able to distinguish between low fall risk older adults and high fall risk older adults on the tandem stance and single leg conditions. These results suggest that an older adult's ability to successfully perform tandem and single leg stances for 30 seconds could potentially distinguish between low and high fall risk older adults. It is important to note that this method might not be safe to use in real world settings unless trained clinicians or researchers are present.

Additional results about smartphone usage in this population are promising. 86% of older adults reported using a smartphone capable of powering a balance application. This is significantly higher than previous reports of 27% of smartphone use by older adults in 2015 (Smith, 2015). Our sample is on the younger side of older adults and likely more educated than the general public based on the close proximity to a university campus. Indeed, within the older adults, seven reported having a PhD, 16 reported having a master's degree, four reported having a bachelor's degree, one reported having an associate's degree, and two reported completing high school as their highest level of education. In addition, all participant volunteered for research evaluating a smartphone balance application. Therefore, they had some vested interest in smartphones and the application to begin with. This could explain the discrepancy in percentage of adults owning a smartphone as reported here. Moreover, within the high fall risk older adult group, 83% responded "yes" when asked if they would consider using a smartphone powered balance application in the future. These results demonstrate the high demand and available infrastructure for a smartphone based balance screener in this population.

While the study successfully tested a novel smartphone powered balance application, it is not without limitations. As previously mentioned, the sample was fairly young compared to other geriatric research, highly educated and predominately female. Caution should be taken when generalizing these results to the broader geriatric population. Additionally, the current study did not examine usability of the application. Lastly, the application was tested in a controlled laboratory setting. It is not clear if the results would be replicated in a real-world environment – which is the intended use for the app.

The purpose of this thesis was test a novel smartphone balance assessment application in young and old adults. The application was successfully tested in young adults, low fall risk older adults, and high fall risk older adults. The application was significantly correlated to posturographic measures and was able to distinguish between low fall risk and high fall risk older adults. The ability to distinguish between these groups may be improved with different accelerometry measures, such as the peak-to-peak ratio, 95% confidence ellipsoid volume, and normalized path length due to their significant results in previous mobile device validation studies (Kosse et al., 2015; Ozinga & Alberts, 2014; Ozinga et al., 2015). Additionally, behavioral measures, such as willingness to attempt a challenging balance task should be examined as well. A review of the current literature revealed a need for further research to also include measures of reliability and usability within the target audience.

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